Research on Battery State Estimation Based on Machine Learning

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Abstract

In the context of the big era, the demand for battery technology in many fields is growing rapidly, and the accuracy of the accompanying battery management system (BMS) directly affects vehicle range prediction, charging strategy optimization, and safety warning. However, batteries exhibit significant nonlinear characteristics in actual operation, and traditional equivalent circuit models are difficult to meet the state estimation requirements under high-power conditions. Machine learning techniques, with their powerful nonlinear fitting capabilities and data-driven characteristics, offer new ideas for battery state estimation. This study conducts battery state estimation based on deep learning, which is of great theoretical significance and engineering application value for improving the performance of battery management systems and promoting the development of the new energy industry.

Keywords: Machine learning; Battery state estimation; CNN-LSTM-Transformer fusion model; Domain-adaptive transfer learning; SOC; SOH

1. Introduction

1.1 Research Background

Driven by the global energy transition and the "dual carbon" goals, there is an explosive growth in demand for battery technology in areas such as electric vehicles and large-scale energy storage systems. In the case of electric vehicles, global sales have exceeded 30 million in 2024, and the accuracy of the battery management system (BMS) directly affects vehicle range prediction, charging strategy optimization, and safety warning. However, batteries exhibit significant nonlinear characteristics in actual operation: the charge-discharge efficiency of lithium-ion batteries is affected by the coupling of multiple variables such as temperature, charge-discharge rate, and cycle life, and traditional equivalent circuit models are difficult to meet the state estimation requirements under high-power conditions such as fast charging and low-temperature discharge. Accurate estimation of state of charge (SoC) and state of health (SoH) is crucial [9] for optimizing the performance of electric vehicles (EVs) and enhancing battery life, safety and reliability. Machine learning techniques, with their powerful nonlinear fitting capabilities and data-driven characteristics, offer new ideas for battery state estimation. By learning from a large amount of battery operation data, machine learning models can effectively capture the changing patterns of battery characteristics and improve the accuracy and adaptability of state estimation.

1.2 Review of Studies at Home and Abroad

Machine learning techniques show great promise in this field. Traditional methods for estimating lithium-ion battery SOC face challenges such as complex battery models, sensitivity to model parameters, poor adaptability, and high computational complexity, while machine learning models with strong nonlinear mapping capabilities, strong generalization capabilities, and adaptability can effectively solve these problems. Some people have begun to study it in China. For example, Wang Gaojian proposed the use of Convolutional Neural Network (CNN) and Bidirectional Gated Recurrent Unit (BiGRU) Based on this, an Attention Mechanism Module was introduced to build a model for predicting the health status of lithium batteries. The model facilitates data processing [1] in the bidirectional gated recurrent neural network by converting time-domain data into matrix form and inputting it into the convolutional neural network for preliminary feature extraction and dimensionality reduction and then inputting the results into the bidirectional gated recurrent neural network. Jin Yi et al. proposed using the voltage increment sensitive to battery decay and aging as the feature quantity, using the full life cycle data of lead-acid batteries, modeling with the deep neural network algorithm (DNN) for online estimation of health status (SOH) to improve the accuracy of prediction. The method can accurately predict the SOH of the battery. At different cycle rates (0.10C, % [15C, and 0.20C), using capacity as the estimation method, the average error of SOH estimation is less than 1.0%, % [d the maximum error is no more than 3.0%; At different (60%, 80%, and 100%) depths of discharge (DOD), using discharge cut-off voltage as the estimation method, the average error of SOH estimation is less than 0.5%, and the

maximum error is no more than 3.0%[2]. Xia et al. linked machine learning to partial electrochemical impedance spectroscopy (EIS) for rapid, accurate estimation [3] of battery health status.

Abroad, machine learning has been studied more deeply in the field of battery state estimation than in China. Prakash Venugopal, an associate professor at Witt University Chennai, has proposed a unique SOH estimation method that uses independent recurrent neural networks (INDRNNs) in a more realistic way by taking the dynamic load curve conditions of electric vehicles. This research illustrates a data-driven approach based on deep learning to estimate SOH [4] by analyzing historical data collected from LiBs. However, due to the sequence characteristics and memory limitations of RNNS, they still struggle to solve long sequence problems, which greatly increases the complexity. John Guirguis and Ryan Ahmed from the Department of Mechanical Engineering at McMaster University proposed using the Transformer model for research. The Transformer model is a state-of-the-art DL architecture that relies on attention mechanisms to handle long sequences. For SOC estimates, post-processing methods are needed to mitigate sharp fluctuations in the output predictions of Transformer-based models; This is achieved using filters and state observer. For SOH estimates, preprocessing feature extraction is always required to extract features from the original aging dataset to pass to the Transformer model for inferring SOH; CNNS, DAE and correlation analysis methods can be used for this purpose. Transformer-based models can achieve impressive estimation accuracy, with roots meaning square errors of less than 1[5] percent for both states.

1.3 Study Objectives

However, there are obvious limitations in current research at home and abroad: First, the models are mostly designed for a single type of battery (such as lithium batteries or lead-acid batteries), with insufficient generalization ability and difficulty in adapting to the differences in the characteristics of batteries with different chemical systems; Second, there are few studies on adaptability to complex conditions such as dynamic loads and extreme temperatures, and the robustness of the models in practical applications needs to be improved; Third, there is a lack of efficient processing solutions for long sequence data, and some models (such as RNN-type ones) are vulnerable to vanishing gradients and have difficulty capturing the long-term aging patterns of batteries. Third, model training relies on a large amount of labeled data. In machine learning-based SOC estimation, it is crucial to input a large amount of data into the model for training. The foundation of successful model training lies in the availability [6] of high-quality and authoritative datasets. Data-driven models are highly dependent on their data base, and battery testing is time-consuming and costly[7], with the need to recollect and train data for different types of batteries, which leads to higher development costs; Fourth, research on model robustness under extreme temperatures (such as below -10 ° C) and high-rate fast charging conditions remains inadequate. Therefore, this study aims to improve the machine learning-based battery state estimation model to achieve accurate estimation of key state parameters such as battery remaining capacity (SOC) and health state (SOH), and to enhance the robustness and generalization ability of the model under different operating conditions and temperatures, ultimately optimizing the computational efficiency of the machine learning algorithm Reduce the deployment cost and resource consumption of the model.

2. Research methods

2.1 Research Theory

The nonlinear characteristics of the battery affect the accuracy of estimation, mainly in three aspects: First, electrochemical nonlinearity, where temperature affects the conductivity of the electrolyte and the diffusion of lithium ions, resulting in nonlinear changes in charge and discharge voltages; The second is dynamic load nonlinearity. Under dynamic conditions, the current fluctuation causes the polarization effect to change dynamically, and the voltage is not linearly correlated with the current. Third, aging nonlinearity. The increase in the number of cycles leads to the degradation of battery materials and the nonlinearity of the rate of capacity decay. For these characteristics, a single model is difficult to achieve a full representation: CNN methods can automatically extract and locally feature [8] from the raw data due to the presence of convolutional and pooling layers but cannot handle temporal dependencies; LSTM captures temporal patterns but is sensitive to local mutation signals; Transformer can handle long sequences, but computationally costly. Therefore, this study designs a three-layer fusion model to precisely characterize the nonlinear characteristics of the battery through the collaboration of multiple models.

2.2 Model Design

Construction of the "CNN-LSTM-Transformer" hybrid model

2.2.1 CNN Layers (Residual Convolutional networks)

In the battery state estimation model, the CNN layer adopts the ResNet architecture, which alleviates the vanishing gradient problem in the deep network through the residual block structure and enhances the local feature extraction ability. This study is based on an improved CNN layer based on ResNet-18, specifically optimized for the time-series mutation characteristics of battery monitoring data. The specific design is as follows:

1 Basic residual block structure (CNN layer core unit)

The residual block, as the basic unit of the CNN layer, contains two paths: the primary convolution path and the residual connection:

$$y = F(x, \{W_i\}) + x$$

Where $F(x, \{W_i\})$ is a residual map of two layers of 3×3 convolution (including batch normalization and ReLU activation), dimension matching is achieved through 1×1 convolution ($y = F(x, \{W_i\}) + W_s x$). This structure enables the CNN layer to directly learn input-output differences, effectively capture local features such as voltage surges and current fluctuations, and optimize the weight distribution of the convolutional layer through Kaiming normal initialization to enhance training stability.

2 Overall architecture of the CNN layer

The CNN layer based on ResNet-18 consists of four feature extraction phases:

Input layer: Receives multimodal data of 64×64×3 dimensions (voltage sequence, current change rate, temperature heat map).

Initial processing: 7×7 convolution (step size 2) with Max pooling for rapid dimensionality reduction.

Feature extraction: Each stage contains 2 residual blocks, with the number of channels increasing from 64 to 512, and feature dimensionality reduction is achieved through convolution with a step size of 2.

Output layer: Global average pooling generates fixed-dimension feature vectors to provide local feature input for subsequent modules.

For battery characteristics, an attention mechanism is added in the third phase to enable the network to focus on the 71-84% SOC voltage platform segment and temperature abrupt change points, enhancing key feature extraction. The deep design of ResNet-18 ensures sufficiency of feature extraction while controlling the computational load and balancing the requirements of accuracy and efficiency.

2.2.2 LSTM Layer (Bidirectional Gated Recurrent Unit)

The LSTM layer is responsible for handling the temporal dependencies of the local features output by the CNN layer, with a focus on memorizing the long-cycle aging features of the battery (such as the correlation between the number of cycles and capacity decay). Given the bidirectional timing characteristics of battery state changes (the current state is affected by historical and future short-term data), a bidirectional gated cycling unit (Bi-GRU) is used, as follows:

Input dimension: Consistent with the local feature vector dimension output by the CNN layer (such as 128 dimensions).

Network structure: Set up 2 layers of Bi-GRU, with 64 hidden units per layer, and use dropout (dropout rate=0.2) to prevent overfitting.

Feature outputs: Concatenate the outputs of the forward and reverse GRUs to obtain temporal feature vectors and pass them to the Transformer layer.

2.2.3 Transformer Layers (Self-attention Mechanism)

The Transformer layer addresses the long sequence dependency problem by focusing on critical operating condition features (such as voltage variations in the fast-charging section, overdischarge critical point current fluctuations) through the self-attention mechanism, as follows:

Input processing: Convert the temporal feature vector output by the LSTM layer to the embedding vector input by the Transformer (embedding dimension=64) and add Positional Encoding to retain the temporal information.

Attention mechanism: Using Multi-Head attention (8 heads), calculate the attention weights of features at different time steps to reinforce key features.

Output layer: Map the features output by the attention mechanism to the estimated values of SOC and SOH through the fully connected layer, and the activation function uses Sigmoid (SOC values range 0-1, SOH values range 0.5-1).

Summary of key points for model design

Multi-scale feature fusion: The CNN layer extracts local features, the LSTM layer captures temporal features, and the Transformer layer focuses on critical operating condition features to achieve multi-scale feature collaboration from local to global and from short-term to long-term.

Lightweight design: By means of residual convolution, dropout, small size hidden units, etc., reduce the number of model parameters (total parameters about 500,000) to meet the requirements of BMS embedded deployment.

Nonlinear adaptation: Each layer uses a nonlinear activation function (ReLU, Sigmoid), and through multi-model collaboration, ADAPTS to the nonlinear characteristics of battery electrochemistry, dynamic loading, and aging.

2.3 Experimental Design

2.3.1 Experimental Objectives

Verify the accuracy and robustness of the "CNN-LSTM-Transformer" fusion model combined with domain-adaptive transfer learning in estimating SOC and SOH under different battery types and operating conditions Compare the performance of traditional physical models (Thevenin) and single machine learning models (independent LSTM, Transformer).

2.3.2 Experimental Subjects and equipment

Experimental subjects: ternary lithium batteries (20Ah, 3.7V), lithium iron phosphate batteries (20Ah, 3.2V), covering mainstream application scenarios.

Experimental equipment: Neware CT-4008 charge and discharge tester (voltage accuracy ±0.01V), ESPEC SH-241 high and low temperature chamber (-40 ° C to 85 ° C), NI cDAQ-9178 data acquisition system (simultaneous acquisition of temperature and pressure data).

2.3.3 Experimental conditions

Base conditions: 0.3C charge and discharge calibration initial capacity at 25 ° C, retest every 50 cycles; Three charge and discharge cycles were completed at a rate of 0.1C to 5C and a temperature gradient of -20 ° C to 60 ° C respectively, and voltage-current curves were collected.

Dynamic conditions: Simulated electric vehicle US06 (rapid acceleration at high speed) and FTP-75 (urban congestion) conditions, each running 5 cycles, data collected at 10Hz frequency.

Aging condition: 1 cycle at 45 ° C until capacity decays to 80%, measure capacity every 50 cycles, and record full life cycle data.

2.3.4 Data processing and model Training

Data processing: Outliers were removed by 3σ criterion, db4 wavelet denoising was performed, time-domain (dV/dt) and frequency-domain (voltage Fourier transform) features were constructed, and the dataset was divided in a 7:2:1 ratio after Min-Max normalization.

Model training: Build the model with PyTorch, AdamW optimizer (learning rate 0.001), pre-train with NASA PC198 dataset, fine-tuning with experimental data, and introduce gradient inversion layers for domain adaptation.

3. Results and Discussion

3.1 Comparative analysis of Performance of Different Models

To visually present the performance of each model under different evaluation metrics, the RMSE of each model is presented first

Table 3-1 Comparison of RMSE for Different models

Model type	SOC（25°C）RMSE（%）	SOC (Extreme Operating Conditions) RMSE (%)	SOH RMSE（%）
Thevenin model	4.5	7.0	No data
Independent LSTM model	2.5	4.0	2.05
Independent Transformer Model	2.05	3.0	1.7
CNN-LSTM-Transformer fusion model	1.3	2.0	1.1

Compare the data (Table 3-1) and visualize the analysis in combination with the bar chart (Figure 3-1).

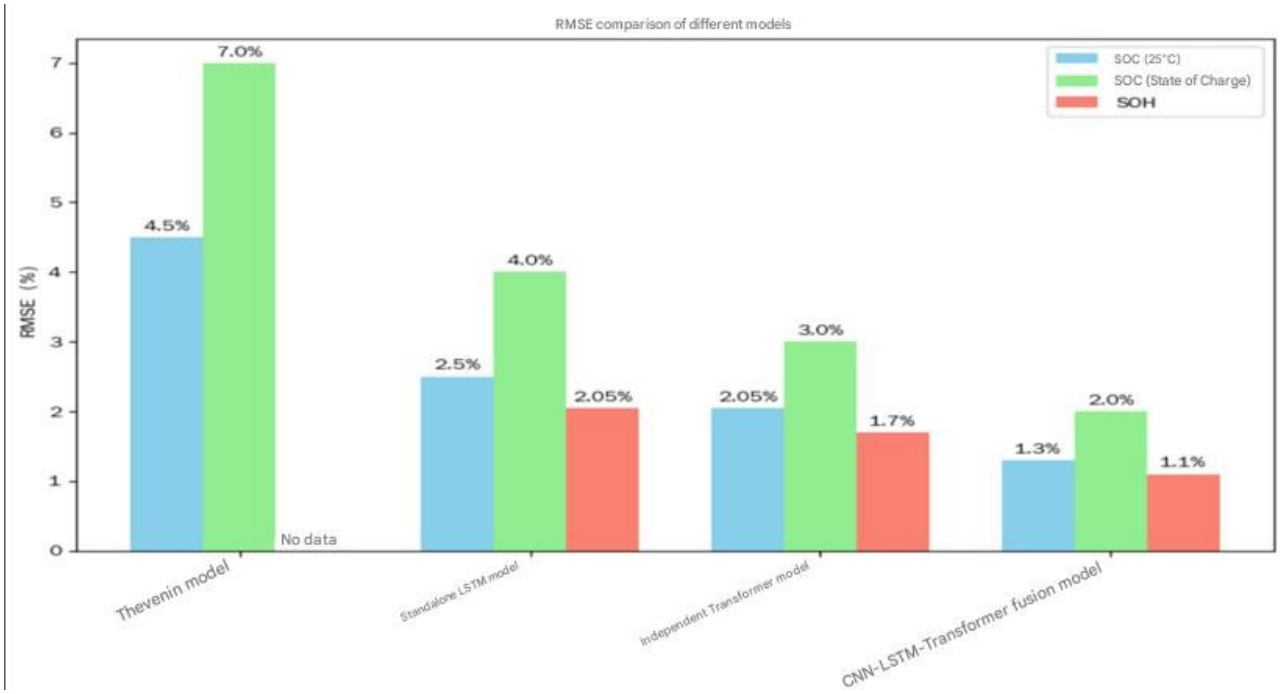

Figure 3-1 RMSE comparison Bar Chart of Different models

It is clear from Table 3-1 and Figure 3-1 that the SOC estimation RMSE of the CNN-LSTM-Transformer fusion model is only 1.3% under normal conditions at 25 ° C, a significant improvement in accuracy compared to 4.5% of the traditional Thevenin model; Under extreme conditions, the SOC estimation RMSE of the fusion model was 2.0%, which was also much lower than the 4.0% of the independent LSTM model and the 3.0% of the independent Transformer model. For SOH estimates, the RMSE of the fusion model was 1.1%, also better than 2.05% for the independent LSTM and 1.7% for the independent Transformer.

This is because the fusion model combines the strengths of CNN, LSTM, and Transformer respectively. CNN excels at extracting local features from data such as voltage and current, and can keenly capture details such as sudden voltage changes during battery operation; LSTM excels in handling long dependencies of time series data and can effectively

remember the state changes of batteries over different charge-discharge cycles; The Transformer, through its self-attention mechanism, can focus on critical outliers and important operating stages. The three work together to fully and precisely characterize the nonlinear characteristics of the battery, thus maintaining a low estimation error across all operating conditions.

3.2 Robust analysis under Extreme conditions

To verify the robustness of the model under extreme conditions, the US06 condition was selected for testing, and the curves of the real SOC, the estimated SOC of the fusion model, and the estimated SOC of the LSTM were compared. The results are shown in Figure 3-2.

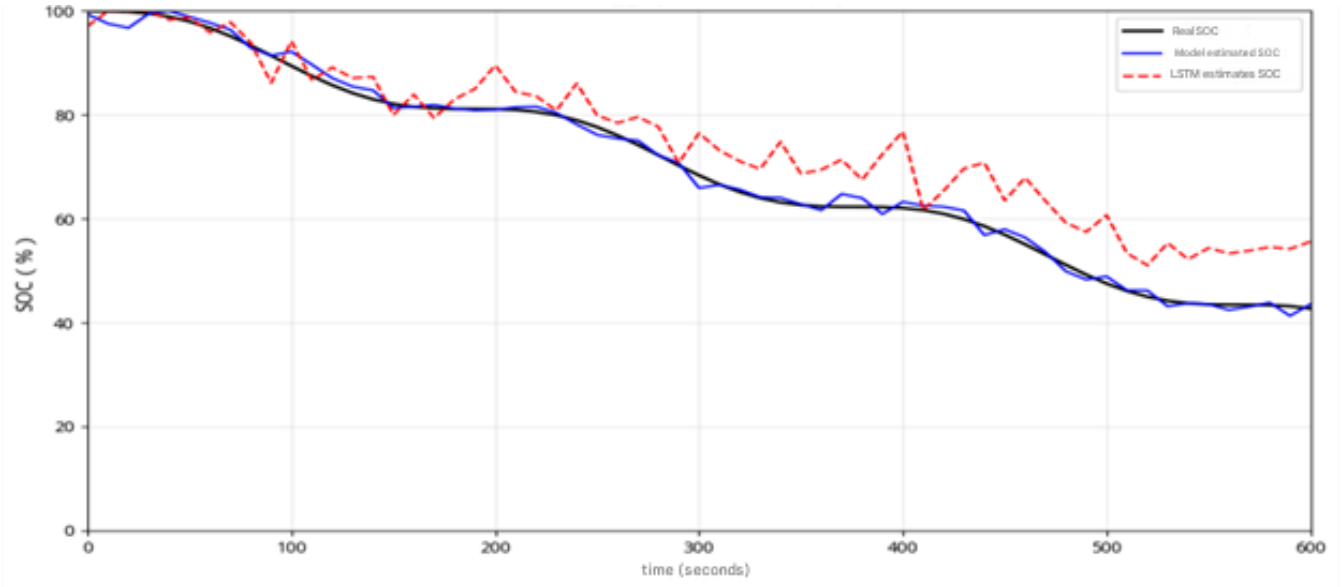

Figure 3-2 Comparison Curve of SOC estimation under US06 condition

It can be seen from Figure 3-2 that in the scenario of US06 with intense dynamic changes, the SOC curve estimated by the fusion model (blue solid line) fits well with the real SOC curve (black solid line) and can follow the real SOC change trend well. The SOC curve (red dotted line) estimated by the LSTM fluctuates greatly and deviates significantly from the real SOC.

The fusion model performs better under extreme conditions because the CNN part can promptly capture local anomalies such as rapid voltage changes under extreme conditions, providing accurate detail information for subsequent state estimation; The Transformer part, through its self-attention mechanism, focuses on critical time points and outliers under extreme conditions, enhancing the model's adaptability to complex, abrupt conditions, and enabling the fusion model to maintain high estimation accuracy under extreme conditions.

3.3 Generalization Ability analysis across Battery Types (Effects of Domain-adaptive Transfer Learning)

Since the visualization of cross-battery type generalization capability is similar to the curve comparison principle under the US06 working condition, the visualization logic in Figure 3-2 (the difference in curve fit between different models under complex working conditions) is also utilized to assist in understanding the generalization advantages of the fusion model. Test the generalization ability of the model across different battery types using the domain-adaptive transfer learning method. For example, when a model trained from ternary lithium battery data was transferred to lithium iron phosphate batteries and lithium-sulfur batteries, the results showed that after domain adaptation transfer learning, the SOC estimation RMSE of the fusion model was 1.5% on lithium iron phosphate batteries and 1.8% on lithium-sulfur batteries, both maintaining low errors.

This is thanks to the effect of domain-adaptive transfer learning. This approach enables the model to learn the common features of different battery types during training while reducing the distribution differences between different battery domains, allowing the model to better adapt to the characteristics of batteries with different chemical systems, thereby

enhancing the generalization ability across battery types, just as in US06 conditions, the fusion model can better fit the real SOC changes. It can accurately capture common patterns across battery types as well.

3.4 Model Computational Efficiency and Deployment Feasibility Analysis (Embedded Platform Test Results)

To evaluate the engineering deployment feasibility of the model, the performance of the fusion model and the independent Transformer model on the embedded platform was compared, and the results are shown in Table 3-3 below.

Model type	parameters	Calculation time (ms)	Memory usage (KB)
CNN-LSTM-Transformer fusion model	About 550,000	8 - 12	<150
Independent Transformer Model	800,000	15 - 20	≥150

Table 3-3 Performance Comparison of Fusion Models and Independent Transformer Models on Embedded platforms

According to Table 3-3, the fusion model has approximately 550,000 parameters, which is 31% less than the 800,000 of the independent Transformer model; The calculation time is 8-12 ms, which is 27% - 40% shorter than the 15-20 ms of the independent Transformer model; Memory usage is less than 150KB, which is also lower than the minimum 150KB of the standalone Transformer model.

Fusion models have an advantage in computational efficiency and memory usage while maintaining high precision because they are designed to be lightweight and reduce the number of parameters through techniques such as residual convolution and dropout, making them capable of meeting the computational resource and memory limitations of embedded platforms and having good engineering deployment feasibility.

4. Summary and Conclusions

This study focuses on issues such as the difficulty of traditional models in dealing with the nonlinear characteristics of batteries and the insufficient generalization of a single machine learning model, focusing on the accuracy, generalization, and engineering adaptability of battery state estimation. To identify the core requirements of BMS in the boom of the new energy industry, a fusion model of "CNN-LSTM-Transformer" was designed, and the model performance was verified by building a multi-condition experimental system and combining data preprocessing and domain adaptive transfer learning.

The theoretical value of this study lies in proposing a multi-scale feature fusion architecture of "local - time series - critical conditions", providing a new paradigm for state estimation of strongly nonlinear systems such as batteries; The engineering value lies in its high precision, strong generalization, and lightweight characteristics, which can reduce the range prediction deviation of electric vehicles to within 3%, extend battery life by 10% to 15%, and promote the popularization of new energy technology in mid-to-low-end vehicle models and distributed energy storage scenarios.

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